Support Vector Machines

Atherosclerotic Heart Disease

In [153]:
```
%matplotlib inline
```

In [25]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm, datasets, preprocessing
from sklearn.preprocessing import scale
import pandas as pd
from pylab import rcParams
rcParams['figure.figsize'] = 20, 10
```

In [82]:
```
heart = pd.read_csv('../data/Heart.csv')
heart.head()
```

Out[82]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [83]:
```
def yes_no(s):
    if s == "Yes":
        return 1
    elif s == "No":
        return 0

heart.AHD.apply(yes_no).head()
```

Out[83]:
```
0    0
1    1
2    1
3    0
4    0
Name: AHD, dtype: int64
```

In [84]:
```
heart['ahd_num'] = heart.AHD.apply(yes_no)
```

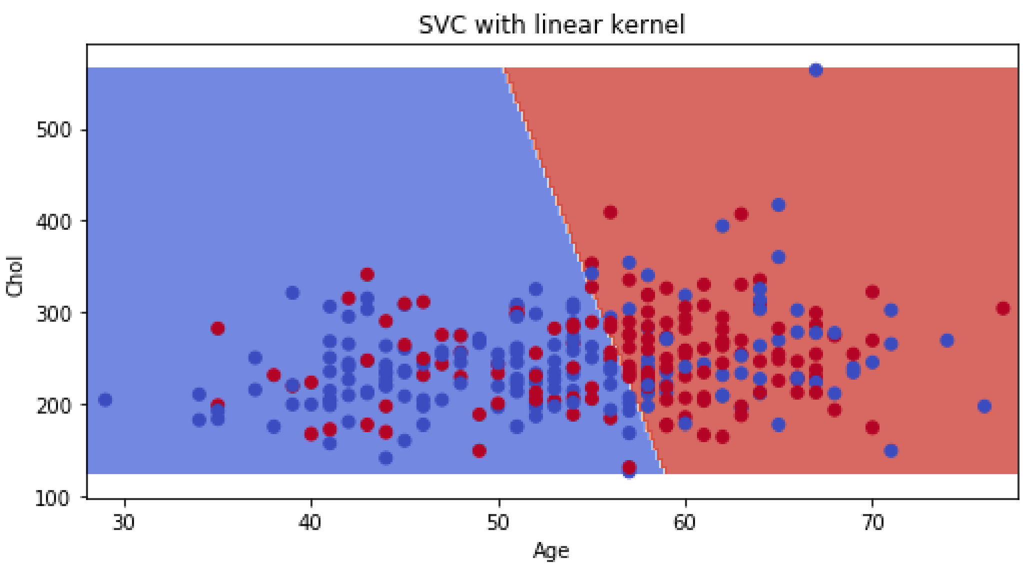
In [85]:
```
heart.head()
```

Out[85]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [122]:
```
def plot_svm(i, clf, title, X, y, col1, col2):

    h = .2  # step size in the mesh
    # create a mesh to plot in
    x_min, x_max = X[col1].min() - 1, X[col1].max() + 1
    y_min, y_max = X[col2].min() - 1, X[col2].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max,
    grid_stack = np.stack([xx.flatten(), yy.flatten()]).T

    x1 = X[col1]
    x2 = X[col2]
    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    plt.subplot(2, 2, i + 1)
    plt.subplots_adjust(wspace=0.4, hspace=0.4)

    Z = clf.predict(scale(grid_stack)).reshape(xx.shape)
    # Put the result into a color plot
    plt.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
    x_s = preprocessing.scale(X)

    # Plot also the training points
    plt.scatter(x1, x2, c=y, cmap=plt.cm.coolwarm)

    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.title(title)
```

In [31]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm, datasets

col1, col2 = 'Age', 'Chol'

X = heart[[col1, col2]]
y = heart['ahd_num']

# we create an instance of SVM and fit out data. We do not scale our data s

svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)


plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)


plt.show()
```



In [32]:
```
C=1.0
X_scaled = preprocessing.scale(X)
```

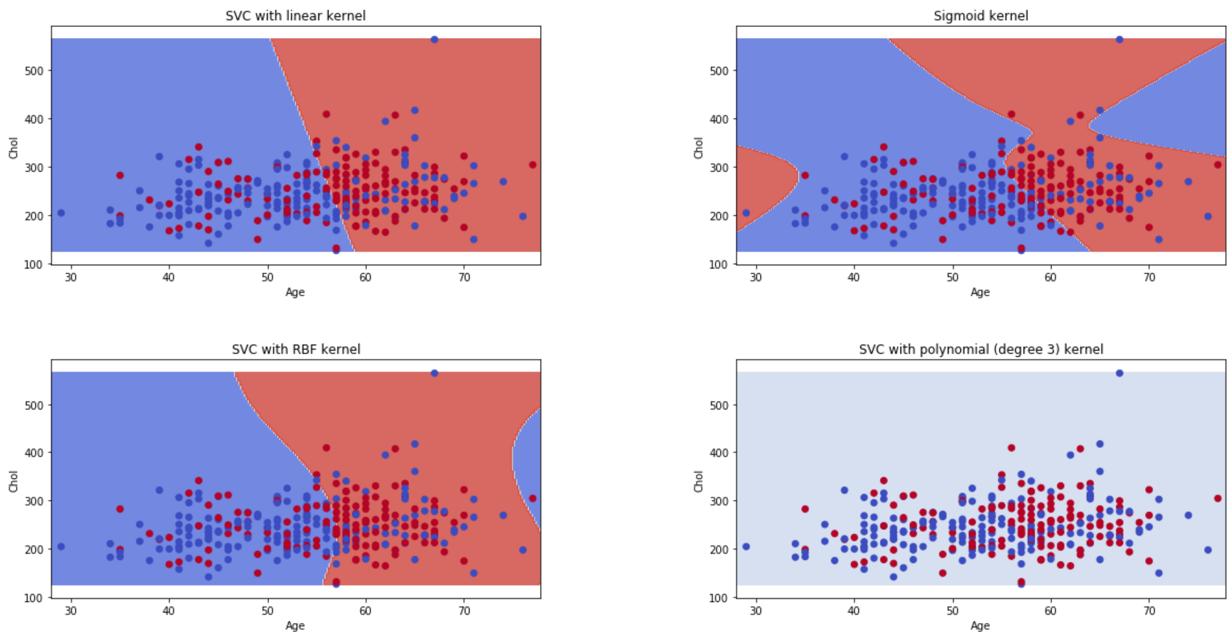
In [33]:
```
svc = svm.SVC(kernel='linear', C=1.0).fit(X_scaled, y)
```

In [34]:
```
rbf_svc = svm.SVC(kernel='rbf', gamma=0.7, C=C).fit(X_scaled, y)
```

In [35]:
```
poly_svc = svm.SVC(kernel='poly', degree=2, C=C).fit(X_scaled, y)
```

In [36]:
```
sig_svc = svm.SVC(kernel='sigmoid', C=C).fit(X_scaled, y)
```

In [37]:
```
# title for the plots
titles = ['SVC with linear kernel',
          'Sigmoid kernel',
          'SVC with RBF kernel',
          'SVC with polynomial (degree 3) kernel']


for i, clf in enumerate((svc, sig_svc, rbf_svc, poly_svc)):
    plot_svm(i, clf, titles[i], X, y, col1, col2)

plt.show()
```



Assignment

1. Convert all columns into new numerical feature columns

In [328]:
```
# ChestPain
heart.ChestPain.unique()
```

Out[328]:
```
array(['typical', 'asymptomatic', 'nonanginal', 'nontypical'], dtype=obje
ct)
```

In [329]:
```
def chestpain(c):
    if c == "typical":
        return 1
    elif c == "asymptomatic":
        return 2
    elif c == "nonanginal":
        return 3
    elif c == "nontypical":
        return 0

heart.ChestPain.apply(chestpain).head()
```

Out[329]:
```
0    1
1    2
2    2
3    3
4    0
Name: ChestPain, dtype: int64
```

In [330]:
```
heart['cp_num'] = heart.ChestPain.apply(chestpain)
heart.head()
```

Out[330]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [331]:
```
# # Thal
# # heart.Thal.unique()
# thal_options = list(heart.Thal.fillna('unknown').unique())
# print(thal_options)
# heart['thal_num'] = heart.Thal.fillna('unknown').map(thal_options.index)
```

In [332]:
```
heart.head()
```

Out[332]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [333]:
```
def thal(t):
    if t == "fixed":
        return 1
    elif t == "normal":
        return 2
    elif t == "reversable":
        return 3
    elif t == "nan":
        return 0

heart.Thal.apply(thal).head()
```

Out[333]:
```
0    1.0
1    2.0
2    3.0
3    2.0
4    2.0
Name: Thal, dtype: float64
```

In [334]:
```
heart['thal_num'] = np.nan_to_num(heart.Thal.apply(thal))
heart.head()
```

Out[334]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [335]:
```
heart.thal_num.unique()
```

Out[335]:
```
array([ 1.,  2.,  3.,  0.])
```

In [336]:
```
heart['thal_num'] = heart.thal_num.astype(np.int)
```

In [337]:
```
heart.head()
```

Out[337]:

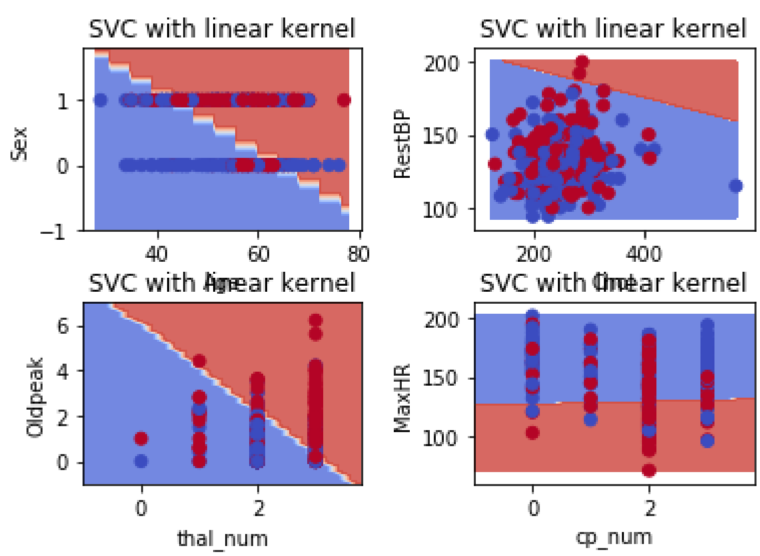
	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

2. Using all the numerical columns:

a) fit a model and plot the resulting predictions.

In [338]:
```
col1_features = ['Age','Chol','thal_num', 'cp_num']
col2_features = ['Sex','RestBP', 'Oldpeak', 'MaxHR']


for i, (col1, col2) in enumerate(zip(col1_features, col2_features)):
    print('Generating: {} vs {}'.format(col1,col2))
    X = heart[[col1,col2]]
    y = heart['ahd_num']

    svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
    plot_svm(i, svc,'SVC with linear kernel' , X, y, col1, col2)
#     plot_svm_nogrid(i, svc,'SVC with linear kernel' , X, y, features[0], 

plt.show()
```

```
Generating: Age vs Sex
Generating: Chol vs RestBP
Generating: thal_num vs Oldpeak
Generating: cp_num vs MaxHR
```



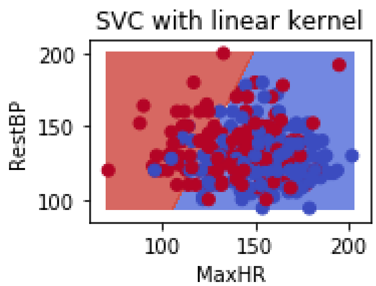
In [339]:

```
# def plot_svm_nogrid(i, clf, title, X, y, col1, col2):

#     h = .2  # step size in the mesh
#     # create a mesh to plot in
#     x_min, x_max = X[col1].min() - 1, X[col1].max() + 1
#     y_min, y_max = X[col2].min() - 1, X[col2].max() + 1
#     xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_ma
#     grid_stack = np.stack([xx.flatten(), yy.flatten()]).T

#     x1 = X[col1]
#     x2 = X[col2]
#     # Plot the decision boundary. For that, we will assign a color to eacl
#     # point in the mesh [x_min, x_max]x[y_min, y_max].
#     plt.subplot(2, 2, i + 1)
#     plt.subplots_adjust(wspace=0.4, hspace=0.4)

# #     Z = clf.predict(scale(grid_stack)).reshape(xx.shape)
# #     # Put the result into a color plot
# #     plt.contourf(xx, yy, Z, cmap=plt.cm.coolwarm, alpha=0.8)
# #     x_s = preprocessing.scale(X)

#     # Plot also the training points
#     plt.scatter(x1, x2, c=y, cmap=plt.cm.coolwarm)

#     plt.xlabel(col1)
#     plt.ylabel(col2)
#     plt.title(title)

# plot_svm_nogrid(0, svc,'SVC with linear kernel' , X, y, features[0], featu

# features = ['Age','Chol','thal_num', 'cp_num', 'MaxHR']
# features = ['Age','Chol', 'thal_num']
# X = heart[features]

heart.head()
```

Out[339]:

	Unnamed: 0	Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slo
0	1	63	1	typical	145	233	1	2	150	0	2.3	
1	2	67	1	asymptomatic	160	286	0	2	108	1	1.5	
2	3	67	1	asymptomatic	120	229	0	2	129	1	2.6	
3	4	37	1	nonanginal	130	250	0	0	187	0	3.5	
4	5	41	0	nontypical	130	204	0	2	172	0	1.4	

In [340]:
```
col1, col2 = 'MaxHR', 'RestBP'

X = heart[[col1, col2]]
y = heart['ahd_num']
# print(X.shape)

# we create an instance of SVM and fit out data. We do not scale our data s
svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
plt.show()
```



In [201]:
```
# col1, col2 = 'cp_num', 'thal_num'

# X = heart[[col1, col2]]
# y = heart['ahd_num']
# # print(X.shape)

# # we create an instance of SVM and fit out data. We do not scale our data
# svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()
```

In [202]:
```
# col1, col2 = 'Fbs', 'RestECG'

# X = heart[[col1, col2]]
# y = heart['ahd_num']
# # print(X.shape)

# # we create an instance of SVM and fit out data. We do not scale our data
# svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()
```

In [203]:
```
# col1, col2 = 'Chol','ExAng'

# X = heart[[col1, col2]]
# y = heart['ahd_num']
# # print(X.shape)

# # we create an instance of SVM and fit out data. We do not scale our data
# svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()

# # This particular graph does not have the line going through any points, s
```

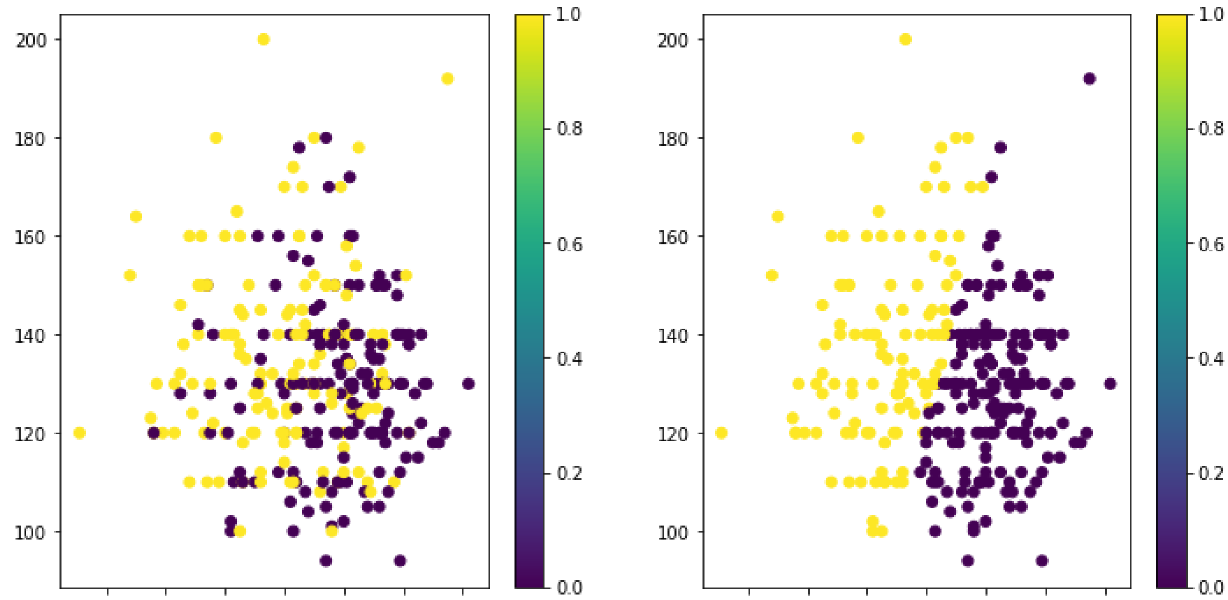
In [198]:
```
# col1, col2 = 'Oldpeak','Slope'

# X = heart[[col1, col2]]
# y = heart['ahd_num']
# # print(X.shape)

# # we create an instance of SVM and fit out data. We do not scale our data
# svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()
```

In [146]:
```
# col1, col2 = 'Age','Ca'

# X = heart[[col1, col2]]
# y = heart['ahd_num']
# # print(X.shape)

# # we create an instance of SVM and fit out data. We do not scale our data
# svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()

# # Cannot plot due to Nan values
```

b) count the number of correct Yes prediction and No prediction along with the number of Wrong Yes/No and store them into a dictionary (see Confusion Matrix for more details).

In [341]:
```
col1, col2 = 'MaxHR', 'RestBP'

X = heart[[col1, col2]]
y = heart['ahd_num']
# print(X.shape)

# we create an instance of SVM and fit out data. We do not scale our data s
svc = svm.SVC(kernel='linear', C=1.0).fit(scale(X), y)
# plot_svm(0, svc,'SVC with linear kernel' , X, y, col1, col2)
# plt.show()

plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
sca = plt.scatter(X[col1], X[col2], c=y, vmin=0, vmax=1)
plt.colorbar(sca)


z = svc.predict(scale(X))

plt.subplot(1,2,2)
sca = plt.scatter(X[col1], X[col2], c=z, vmin=0, vmax=1)
plt.colorbar(sca)
```

Out[341]: <matplotlib.colorbar.Colorbar at 0x111532780>



In [342]:
```
y.head().values, z[:5]
```

Out[342]: (array([0, 1, 1, 0, 0]), array([0, 1, 1, 0, 0]))

In [343]:
```
# y: actual values
# z: predicted values

# Confusion matrix:
# True positives
# tp = sum((y.head() == True) & (z[:5] == True))
tp = sum((y == True) & (z == True))
# print(tp)

# True negatives
# tn = sum((y.head() == False) & (z[:5] == False))
tn = sum((y == False) & (z == False))
# print(tn)

# False positives
# fp = sum((y.head() == False) & (z[:5] == True))
fp = sum((y == False) & (z == True))
# print(fp)

# False negatives
# fn = sum((y.head() == True) & (z[:5] == False))
fn = sum((y == True) & (z == False))
# print(fn)

confusion_dict = {'false positives': fp, 'false negatives': fn, 'true negati

print(confusion_dict)
```

```
{'false positives': 32, 'false negatives': 58, 'true negatives': 132, 'tr
ue positives': 81}
```

In [344]:
```
from sklearn.metrics import confusion_matrix

confusion_mat = confusion_matrix(y,z)
print(confusion_mat)
```

```
[[132  32]
 [ 58  81]]
```

c) repeat this for all the possible Kernels and vary your polynomial degrees

In [345]:
```
# Repeat for all possible kernels

C=1.0
X_scaled = preprocessing.scale(X)

svc = svm.SVC(kernel='linear', C=1.0).fit(X_scaled, y)

rbf_svc = svm.SVC(kernel='rbf', gamma=0.7, C=C).fit(X_scaled, y)

poly_svc = svm.SVC(kernel='poly', degree=2, C=C).fit(X_scaled, y)

sig_svc = svm.SVC(kernel='sigmoid', C=C).fit(X_scaled, y)

kernels = [svc, rbf_svc, poly_svc, sig_svc]
confusion_dicts = []

for kernel in kernels:


#     predicted values
    z = kernel.predict(X_scaled)
#     compared predicted values with actual values
    tp = sum((y == True) & (z == True))
    tn = sum((y == False) & (z == False))
    fp = sum((y == False) & (z == True))
    fn = sum((y == True) & (z == False))
#     create dictionary
    confusion_dict = {'kernel': kernel.kernel,'false positives': fp, 'false
#     print(kernel)
    print(confusion_dict)
#     confusion_mat = confusion_matrix(y,z)
#     print(confusion_mat)
    confusion_dicts.append(confusion_dict)
    print(confusion_dicts)
```

```
{'kernel': 'linear', 'false positives': 32, 'false negatives': 58, 'true
 negatives': 132, 'true positives': 81}
[{'kernel': 'linear', 'false positives': 32, 'false negatives': 58, 'true
negatives': 132, 'true positives': 81}]
{'kernel': 'rbf', 'false positives': 36, 'false negatives': 48, 'true neg
atives': 128, 'true positives': 91}
[{'kernel': 'linear', 'false positives': 32, 'false negatives': 58, 'true
negatives': 132, 'true positives': 81}, {'kernel': 'rbf', 'false positive
s': 36, 'false negatives': 48, 'true negatives': 128, 'true positives': 9
1}]
{'kernel': 'poly', 'false positives': 3, 'false negatives': 126, 'true ne
gatives': 161, 'true positives': 13}
[{'kernel': 'linear', 'false positives': 32, 'false negatives': 58, 'true
negatives': 132, 'true positives': 81}, {'kernel': 'rbf', 'false positive
s': 36, 'false negatives': 48, 'true negatives': 128, 'true positives': 9
1}, {'kernel': 'poly', 'false positives': 3, 'false negatives': 126, 'tru
e negatives': 161, 'true positives': 13}]
{'kernel': 'sigmoid', 'false positives': 61, 'false negatives': 61, 'true
negatives': 103, 'true positives': 78}
[{'kernel': 'linear', 'false positives': 32, 'false negatives': 58, 'true
negatives': 132, 'true positives': 81}, {'kernel': 'rbf', 'false positive
s': 36, 'false negatives': 48, 'true negatives': 128, 'true positives': 9
```

```
1}, {'kernel': 'poly', 'false positives': 3, 'false negatives': 126, 'tru
e negatives': 161, 'true positives': 13}, {'kernel': 'sigmoid', 'false po
sitives': 61, 'false negatives': 61, 'true negatives': 103, 'true positiv
es': 78}]
```

In [346]:
```
#  Vary the polynomial degrees

degrees = list(range(1,15))
print(degrees)

for degree in degrees:
#     run model with varying degrees
    poly_svc = svm.SVC(kernel='poly', degree=degree, C=C).fit(X_scaled, y)
#     predicted values
    z = poly_svc.predict(X_scaled)
#     compared predicted values with actual values
    tp = sum((y == True) & (z == True))
    tn = sum((y == False) & (z == False))
    fp = sum((y == False) & (z == True))
    fn = sum((y == True) & (z == False))
#     create dictionary
    poly_degree = 'poly_{degree}'.format(degree = degree)
    confusion_dict = {'kernel': poly_degree,'true negatives': tn, 'false pos
    print(degree, confusion_dict)
    confusion_mat = confusion_matrix(y,z)
    print(confusion_mat)
    confusion_dicts.append(confusion_dict)
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]
1 {'kernel': 'poly_1', 'true negatives': 131, 'false positives': 33, 'fal
se negatives': 57, 'true positives': 82}
[[131  33]
 [ 57  82]]
2 {'kernel': 'poly_2', 'true negatives': 161, 'false positives': 3, 'fals
e negatives': 126, 'true positives': 13}
[[161   3]
 [126  13]]
3 {'kernel': 'poly_3', 'true negatives': 152, 'false positives': 12, 'fal
se negatives': 101, 'true positives': 38}
[[152  12]
 [101  38]]
4 {'kernel': 'poly_4', 'true negatives': 161, 'false positives': 3, 'fals
e negatives': 121, 'true positives': 18}
[[161   3]
 [121  18]]
5 {'kernel': 'poly_5', 'true negatives': 157, 'false positives': 7, 'fals
e negatives': 108, 'true positives': 31}
[[157   7]
 [108  31]]
6 {'kernel': 'poly_6', 'true negatives': 161, 'false positives': 3, 'fals
e negatives': 124, 'true positives': 15}
[[161   3]
 [124  15]]
7 {'kernel': 'poly_7', 'true negatives': 159, 'false positives': 5, 'fals
e negatives': 110, 'true positives': 29}
[[159   5]
 [110  29]]
8 {'kernel': 'poly_8', 'true negatives': 161, 'false positives': 3, 'fals
e negatives': 124, 'true positives': 15}
[[161   3]
 [124  15]]
9 {'kernel': 'poly_9', 'true negatives': 160, 'false positives': 4, 'fals
```

```
e negatives': 110, 'true positives': 29}
[[160   4]
 [110  29]]
10 {'kernel': 'poly_10', 'true negatives': 161, 'false positives': 3, 'fa
lse negatives': 115, 'true positives': 24}
[[161   3]
 [115  24]]
11 {'kernel': 'poly_11', 'true negatives': 160, 'false positives': 4, 'fa
lse negatives': 109, 'true positives': 30}
[[160   4]
 [109  30]]
12 {'kernel': 'poly_12', 'true negatives': 160, 'false positives': 4, 'fa
lse negatives': 119, 'true positives': 20}
[[160   4]
 [119  20]]
13 {'kernel': 'poly_13', 'true negatives': 160, 'false positives': 4, 'fa
lse negatives': 110, 'true positives': 29}
[[160   4]
 [110  29]]
14 {'kernel': 'poly_14', 'true negatives': 160, 'false positives': 4, 'fa
lse negatives': 111, 'true positives': 28}
[[160   4]
 [111  28]]
```

In [347]:
```
confusion_dicts[:2]
```

Out[347]:
```
[{'false negatives': 58,
  'false positives': 32,
  'kernel': 'linear',
  'true negatives': 132,
  'true positives': 81},
 {'false negatives': 48,
  'false positives': 36,
  'kernel': 'rbf',
  'true negatives': 128,
  'true positives': 91}]
```

3. Using the dictionary into a pandas DataFrame, display the results

In [356]:
```
df = pd.DataFrame(confusion_dicts)
df
```

Out[356]:

	false negatives	false positives	kernel	true negatives	true positives
0	58	32	linear	132	81
1	48	36	rbf	128	91
2	126	3	poly	161	13
3	61	61	sigmoid	103	78
4	57	33	poly_1	131	82
5	126	3	poly_2	161	13
6	101	12	poly_3	152	38
7	121	3	poly_4	161	18
8	108	7	poly_5	157	31
9	124	3	poly_6	161	15
10	110	5	poly_7	159	29
11	124	3	poly_8	161	15
12	110	4	poly_9	160	29
13	115	3	poly_10	161	24
14	109	4	poly_11	160	30
15	119	4	poly_12	160	20
16	110	4	poly_13	160	29
17	111	4	poly_14	160	28

4. Repeat this process with a 65/35 Train/Test Split and using the Test Set for your prediction metrics

In [349]:
```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=.
```

In [350]:
```
X_train.shape, y_train.shape
```

Out[350]: ((106, 2), (106,))

In [351]:
```
# Repeat for all possible kernels

C=1.0
X_scaled = preprocessing.scale(X)

svc = svm.SVC(kernel='linear', C=1.0).fit(X_train, y_train)

rbf_svc = svm.SVC(kernel='rbf', gamma=0.7, C=C).fit(X_train, y_train)

poly_svc = svm.SVC(kernel='poly', degree=2, C=C).fit(X_train, y_train)

sig_svc = svm.SVC(kernel='sigmoid', C=C).fit(X_train, y_train)

kernels = [svc, rbf_svc, poly_svc, sig_svc]
confusion_dicts_65_35_split = []

for kernel in kernels:

#     predicted values
    z = kernel.predict(X_test)
#     compared predicted values with actual values
    tp = sum((y_test == True) & (z == True))
    tn = sum((y_test == False) & (z == False))
    fp = sum((y_test == False) & (z == True))
    fn = sum((y_test == True) & (z == False))
#     create dictionary
    confusion_dict_65_35_split = {'kernel': kernel.kernel,'false positives':

    print(confusion_dict_65_35_split)
    confusion_dicts_65_35_split.append(confusion_dict_65_35_split)
```

```
{'kernel': 'linear', 'false positives': 20, 'false negatives': 44, 'true
 negatives': 85, 'true positives': 48}
{'kernel': 'rbf', 'false positives': 22, 'false negatives': 42, 'true neg
atives': 83, 'true positives': 50}
{'kernel': 'poly', 'false positives': 5, 'false negatives': 85, 'true neg
atives': 100, 'true positives': 7}
{'kernel': 'sigmoid', 'false positives': 29, 'false negatives': 45, 'true
negatives': 76, 'true positives': 47}
```

In [352]:
```
#  Vary the polynomial degrees

degrees = list(range(1,15))
print(degrees)

for degree in degrees:
#     run model with varying degrees
    poly_svc = svm.SVC(kernel='poly', degree=degree, C=C).fit(X_train, y_tra
#     predicted values
    z = poly_svc.predict(X_test)
#     compared predicted values with actual values
    tp = sum((y_test == True) & (z == True))
    tn = sum((y_test == False) & (z == False))
    fp = sum((y_test == False) & (z == True))
    fn = sum((y_test == True) & (z == False))
#     create dictionary
    poly_degree = 'poly_{degree}'.format(degree = degree)
    confusion_dict_65_35_split = {'kernel': poly_degree,'true negatives': tr
    print(degree, confusion_dict_65_35_split)
    confusion_mat = confusion_matrix(y_test,z)
#     print(confusion_mat)
    confusion_dicts_65_35_split.append(confusion_dict_65_35_split)
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]
1 {'kernel': 'poly_1', 'true negatives': 84, 'false positives': 21, 'fals
e negatives': 43, 'true positives': 49}
2 {'kernel': 'poly_2', 'true negatives': 100, 'false positives': 5, 'fals
e negatives': 85, 'true positives': 7}
3 {'kernel': 'poly_3', 'true negatives': 102, 'false positives': 3, 'fals
e negatives': 75, 'true positives': 17}
4 {'kernel': 'poly_4', 'true negatives': 99, 'false positives': 6, 'false
negatives': 77, 'true positives': 15}
5 {'kernel': 'poly_5', 'true negatives': 100, 'false positives': 5, 'fals
e negatives': 75, 'true positives': 17}
6 {'kernel': 'poly_6', 'true negatives': 102, 'false positives': 3, 'fals
e negatives': 81, 'true positives': 11}
7 {'kernel': 'poly_7', 'true negatives': 99, 'false positives': 6, 'false
negatives': 76, 'true positives': 16}
8 {'kernel': 'poly_8', 'true negatives': 93, 'false positives': 12, 'fals
e negatives': 74, 'true positives': 18}
9 {'kernel': 'poly_9', 'true negatives': 98, 'false positives': 7, 'false
negatives': 77, 'true positives': 15}
10 {'kernel': 'poly_10', 'true negatives': 95, 'false positives': 10, 'fa
lse negatives': 77, 'true positives': 15}
11 {'kernel': 'poly_11', 'true negatives': 98, 'false positives': 7, 'fal
se negatives': 77, 'true positives': 15}
12 {'kernel': 'poly_12', 'true negatives': 98, 'false positives': 7, 'fal
se negatives': 77, 'true positives': 15}
13 {'kernel': 'poly_13', 'true negatives': 99, 'false positives': 6, 'fal
se negatives': 78, 'true positives': 14}
14 {'kernel': 'poly_14', 'true negatives': 99, 'false positives': 6, 'fal
se negatives': 76, 'true positives': 16}
```

In [353]:

```
df = pd.DataFrame(confusion_dicts_65_35_split)
df
```

Out[353]:

	false negatives	false positives	kernel	true negatives	true positives
0	44	20	linear	85	48
1	42	22	rbf	83	50
2	85	5	poly	100	7
3	45	29	sigmoid	76	47
4	43	21	poly_1	84	49
5	85	5	poly_2	100	7
6	75	3	poly_3	102	17
7	77	6	poly_4	99	15
8	75	5	poly_5	100	17
9	81	3	poly_6	102	11
10	76	6	poly_7	99	16
11	74	12	poly_8	93	18
12	77	7	poly_9	98	15
13	77	10	poly_10	95	15
14	77	7	poly_11	98	15
15	77	7	poly_12	98	15
16	78	6	poly_13	99	14
17	76	6	poly_14	99	16